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Transfer Learning for Water Quality Classification in Tilapia Biofloc Systems using a Catfish Fuzzy Decision Model

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Abstract

This study proposes a transfer learning framework for water quality classification in tilapia (Oreochromis niloticus) biofloc systems, leveraging a fuzzy inference system (FIS) previously developed and validated for catfish (Clarias gariepinus) biofloc monitoring as the source-domain model. Transfer is performed at the parameter level by shifting the trapezoidal membership-function boundaries to tilapia physiological thresholds, leaving the rule base and inference structure unchanged. Because a Mamdani FIS is knowledge-driven (its parameters are derived from the literature rather than learned from data), evaluation is conducted on a 200-sample literature-anchored synthetic tilapia dataset generated from Scopus-indexed biofloc parameter ranges and anchored to the noise characteristics of real IoT sensors from the same device; the synthetic set acts as a test bench that deliberately covers boundary conditions that are rare and unethical to induce in a live pond. The Transfer-FIS is compared with an Unadapted Source-FIS and a Scratch-FIS optimized entirely on tilapia data. The Transfer-FIS achieves 98.00% accuracy and a macro F1-score of 0.9733; a Wilcoxon signed-rank test over 10-fold cross-validation detects no statistically significant difference from the Scratch-FIS (98.50%, F1 = 0.9790; $p = 1.000$; Cohen's $d \approx 0.21$). Taking Non-Ideal as the positive class, the Transfer-FIS produces zero false negatives (missed alarms) whereas the Scratch-FIS produces three, and the Transfer-FIS reaches ~97% accuracy with only 20 target samples. These findings indicate that parameter-level fuzzy transfer is a viable, data-efficient, and operationally conservative strategy; validation on field-collected tilapia data is identified as the next step.

Keywords: biofloc technology, fuzzy inference system, Oreochromis niloticus, synthetic data, tilapia aquaculture, transfer learning, water quality monitoring

1 Introduction

Aquaculture is one of the fastest-growing food production sectors globally, with Nile tilapia (Oreochromis niloticus) and catfish (Clarias sp.) ranking among the most cultivated freshwater species in Southeast Asia, particularly in Indonesia. Nile tilapia (ikan nila) has specific water-quality requirements to ensure optimal growth and survival. The tolerable pH range for tilapia culture is approximately 6.5–9.0, and growth performance is optimal at pH 7–8, with significant reductions at pH 6 and pH 9 [1], [2], [3]. Deviations outside this range impair growth, alter haematological indices, and increase stress [2], [4], [5]; in biofloc systems specifically, pH 6.5–7.5 yielded the best growth and net yield while maintaining good health status [5]. Tilapia can tolerate the upper part of this range; however, the water should remain well-buffered against rapid fluctuations [2], [6].

Turbidity is another critical parameter in the management of tilapia ponds. High turbidity indicates elevated levels of suspended particles, which affect light penetration and the productivity of phytoplankton that support the fish's natural diet [7], [3]. In clear-water ponds turbidity below about 50 NTU is preferred, whereas biofloc systems operate at intrinsically higher turbidity because suspended microbial flocs are part of the production concept; an operational upper threshold of 150 NTU is therefore adopted here for tilapia biofloc (Table 1). Excessive suspended solids induce structural changes in the gills and are associated with reduced growth [8]. Effective management

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practices, including continuous monitoring and IoT-based control, help keep turbidity within acceptable levels [9].

Temperature is a vital factor influencing the health and growth performance of tilapia. The preferred range for optimal growth is generally 25–30°C, with temperatures above 30°C potentially leading to stress and reduced growth rates [10]. Temperature drives metabolic rate, including oxygen consumption and other physiological functions [11]. Maintaining consistent temperature is essential, as thermal fluctuation exacerbates physiological stress [11]. Implementing systems to monitor and manage water temperature is therefore crucial in maximizing tilapia production within commercial ponds [1], [12].

The adoption of Biofloc Technology (BFT) has gained significant momentum owing to its advantages for maintaining water quality, recycling microbial nitrogen, and reducing water-exchange requirements. However, effective management of biofloc systems depends critically on continuous monitoring and timely classification of water-quality status [13].

Fuzzy logic-based decision systems have demonstrated strong performance in water-quality classification, particularly in aquaculture environments where sensor readings are inherently uncertain and parameter thresholds vary across species and rearing conditions. Previous work by the authors established a fuzzy decision framework for real-time water-quality classification in catfish biofloc systems, distinguishing Ideal from Non-Ideal conditions on the basis of pH, turbidity, and temperature [10].

Despite these advances, a critical limitation remains: most aquaculture monitoring models are designed and validated for a single species, requiring complete reconstruction of decision rules, membership functions, and datasets when applied to a new target species. This species-specificity is a significant barrier to scalability, particularly in resource-limited contexts where data-collection infrastructure is constrained. A second, closely related limitation is data scarcity itself: aquatic monitoring is characterized by low sampling frequency, limited spatial coverage, and high experimental cost, so that labelled datasets for a new species are typically small and dominated by "normal" conditions, while the Non-Ideal states that a monitoring system must detect are rare, and deliberately inducing them in a stocked pond is neither ethical nor practical [14].

Transfer learning offers a principled solution to the first limitation. By leveraging knowledge from a well-characterized source domain and adapting it to a target domain with limited labelled data, transfer learning can substantially reduce the time and cost of deploying classification systems for new species [15]. Synthetic, knowledge-anchored data offer a complementary answer to the second limitation: when a model is knowledge-driven (as a Mamdani FIS is) rather than data-driven, synthetic data serve not to train the model but to exercise its decision boundaries across the full operating envelope, including hazardous states that cannot be produced on demand in the field. This simulation-to-real paradigm is well established in robotics [16], [17], healthcare [18], and smart farming [19], and has recently been applied to tilapia water-quality decision support [20]. While transfer learning has been widely applied in image recognition and remote sensing [21], its application to fuzzy-based aquaculture monitoring remains largely unexplored.

This study therefore proposes a transfer-learning framework for water-quality classification in tilapia biofloc systems that uses the previously validated catfish fuzzy decision model as the source domain. The framework involves (1) structural transfer of the fuzzy rule base and inference engine from the catfish model, (2) parameter-level adaptation of the trapezoidal membership-function boundaries using tilapia-specific thresholds derived from Scopus-indexed biofloc literature, and (3) evaluation on a literature-anchored synthetic tilapia dataset against two baselines: an Unadapted Source-FIS and a Scratch-FIS optimized entirely on tilapia data. The contributions are: (i) the first investigation, to the authors' knowledge, of parameter-level FIS transfer across fish species in biofloc monitoring; (ii) a transparent and reproducible synthetic-evaluation protocol with an explicit argument for its validity; (iii) a safety-oriented evaluation in which Non-Ideal is the positive class and missed alarms (false negatives) are the primary risk metric; and (iv) a learning-curve analysis quantifying the data efficiency of transfer.

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2 Related Work

2.1 Water Quality Monitoring in Aquaculture Systems

Effective water-quality management is a cornerstone of productive and sustainable aquaculture. Conventional monitoring relies on periodic manual measurements of physicochemical parameters, which are insufficient to detect rapid fluctuations in intensive biofloc systems. The integration of computational intelligence has substantially improved the expressiveness and adaptability of water-quality decision systems, shifting from simple threshold-based alerts to data-driven and hybrid approaches that learn from historical observations while accommodating measurement uncertainty [22], [23].

2.2 Fuzzy Logic Systems for Aquaculture Water Quality Classification

Fuzzy logic systems are particularly well suited to water-quality assessment because they model continuous, overlapping parameter ranges with linguistic variables and produce interpretable outputs aligned with expert decision-making [24]. Several studies have applied Mamdani-type FIS architectures to classify pond water quality in tilapia and other freshwater farms, incorporating parameters such as dissolved oxygen, pH, temperature, turbidity, and ammonia [25], [26], [27], [28]. Beyond freshwater species, fuzzy logic has also been combined with data-driven classifiers to automate water-quality recovery in brackish-water shrimp ponds: a recent study coupled a K-Nearest Neighbors diagnostic module with fuzzy control of aerators, pumps, and drainage for Vannamei shrimp (Litopenaeus vannamei), reporting 95% diagnostic accuracy [29], underscoring the continuing relevance of fuzzy decision logic for real-time water-quality management across aquaculture species. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) further extend this capability by enabling data-driven optimization of membership-function parameters.

The authors' prior work established a fuzzy decision framework for catfish (Clarias sp.) biofloc systems, monitoring pH, temperature, and turbidity via IoT sensors and classifying water quality as Ideal or Non-Ideal using a Mamdani FIS [10]. In that study the system output agreed with the field operator's assessment on all sampled readings and was validated against field sensor data. This model serves as the source domain for the transfer-learning framework proposed here; its re-evaluation under the harmonized labelling protocol of the present study is reported in Section 4.1.

2.3 Machine Learning Approaches for Tilapia Water Quality Management

The application of machine learning to tilapia aquaculture has grown considerably, driven by the global commercial importance of O. niloticus. A recent contribution benchmarked six algorithms (Random Forest, Gradient Boosting, XGBoost, Support Vector Machines, Logistic Regression, and Neural Networks) together with a Voting Classifier ensemble for tilapia water-quality management decisions, using a scenario-based synthetic dataset balanced with SMOTE-Tomek [20]. Deep learning approaches such as LSTM networks have also been explored for time-series forecasting, but they require substantially larger datasets than fuzzy or shallow models and are sensitive to limited historical records [30].

2.4 Synthetic and Simulation-Derived Data for Evaluation under Data Scarcity

Synthetic data have become an accepted instrument in domains where real labelled data are scarce, costly, privacy-restricted, or dangerous to acquire. In medicine, synthetic data are used to augment rare conditions and to stress-test models before deployment [18]. In robotics, the simulation-to-real (sim-to-real) paradigm trains or verifies controllers in randomized simulations whose parameter distributions deliberately cover the range of conditions expected in reality; when the synthetic distribution is broad enough to contain the real operating envelope, the resulting models transfer to physical systems, and the residual "reality gap" is closed with a small amount of real data [16], [17]. In smart farming, variational autoencoders and generative adversarial networks are used to generate synthetic agronomic records that mimic real-world conditions when labelled data are limited [19]. Reviews of machine learning under small-data conditions in aquatic environments explicitly recommend knowledge-driven data augmentation and transfer learning as the primary remedies for

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low monitoring frequency and high experimental cost [14]. Within tilapia aquaculture, Alnemari et al. built and cross-validated a decision-support system entirely on a scenario-based synthetic dataset [20].

Two properties of the present study make synthetic evaluation particularly appropriate. First, the model under test is a knowledge-driven Mamdani FIS whose membership-function parameters are fixed a priori from physiological literature (Section 3.3); the synthetic data therefore never influence the Transfer-FIS design and cannot be "memorized" by it. Their role is that of a verification test bench that exercises every region of the input space, exactly as randomized simulation is used to verify controllers before field deployment. Second, the labels of the synthetic samples are defined by a crisp threshold rule derived from the same literature, so that the evaluation measures a well-posed question, namely whether the transferred fuzzy decision surface reproduces literature-defined tilapia tolerances, including at boundary and multi-parameter-violation conditions that occur rarely in a healthy pond and that cannot ethically be induced in a stocked one. Field validation remains necessary to quantify the reality gap and is planned as the next step.

2.5 Transfer Learning in Environmental and Biological Monitoring

Transfer learning is formally defined as improving learning in a target domain by leveraging knowledge from a related source domain [15]. In environmental monitoring it has been applied to land-cover mapping, crop-type classification, and air- and water-quality estimation, consistently improving target-domain performance relative to models trained from scratch, particularly when target labels are scarce [21]. Within fuzzy systems, multiple-source fuzzy transfer learning and source-free fuzzy domain adaptation have shown that fuzzy rule structures can be reused across domains with limited target data [31], [32].

Transfer strategies are broadly categorized as instance-based, feature-based, parameter-based, and relational [15]. This study employs parameter-based transfer, adapting the membership-function boundaries of the source fuzzy model using species-specific physiological thresholds. To the best of the authors' knowledge, no prior study has investigated the transferability of FIS parameters across fish species in biofloc aquaculture monitoring, which represents the novel contribution of this work.

3 Methodology

3.1 Source Domain: Catfish Biofloc Fuzzy Decision Model

The source domain consists of real monitoring data and a Mamdani-type FIS developed for catfish (Clarias gariepinus) biofloc systems [10]. Three water-quality parameters are monitored: pH, turbidity (NTU), and water temperature (°C). The FIS employs trapezoidal membership functions defining three linguistic terms per input (Acid/Neutral/Alkali for pH; Low/Intermediate/High for turbidity; Cold/Intermediate/Hot for temperature) and produces two output classes, Ideal and Non-Ideal. The catfish source dataset comprises 20 real IoT sensor samples collected on 7 June 2024 between 00:30 and 10:00 with the monitoring device shown in Fig. 1.

Two accuracy figures are associated with this source model and must be distinguished. In the original study [10], the FIS output agreed with the field operator's assessment on all 20 samples (100%); the operator's judgement served as the ground truth and accepted pH values slightly below 6.5 as tolerable for catfish. In the present study, the same 20 samples are re-scored against the harmonized crisp threshold protocol of Table 1 (pH 6.5–8.5, 25–30°C, <200 NTU) so that the source and target domains share an identical labelling rule. Under this stricter protocol, three samples with pH 6.00, 6.15, and 6.20 are labelled Non-Ideal, and the source FIS classifies them as Ideal, yielding the 85.00% accuracy reported in Section 4.1. The two figures are therefore not contradictory; they reflect two labelling protocols, and the harmonized protocol is used throughout this paper.

3.2 Target Domain: Literature-Anchored Synthetic Tilapia Dataset

No field-labelled tilapia biofloc dataset with the same three sensors was available at the time of the study, and Non-Ideal conditions cannot be deliberately induced in a stocked pond. The target domain therefore comprises 200 synthetic samples generated by the following protocol.

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First, the Operating envelope is determined. Species-specific tolerance ranges for O. niloticus in biofloc systems were taken from Scopus-indexed literature [33], [5], [34] and are summarized in Table 1 together with the catfish ranges used for the source domain.

Second, Sampling is set. Each sample is a triple (pH, turbidity, temperature). For each parameter, values were drawn independently from a mixture of (a) a uniform distribution over the tilapia tolerance band (Table 1) and (b) uniform distributions over the adjacent out-of-range bands (pH 5.0–6.5 and 8.5–10.0; turbidity 150–250 NTU; temperature 20–26°C and 30–36°C), with the mixture weight chosen so that approximately one quarter of the samples violate at least one threshold. The out-of-range bands extend to values that are physiologically stressful but still within the measurement span of the sensors in Fig. 1.

Third, Sensor realism is determined. The empirical spread of the 20 real IoT readings of the source device (standard deviation of successive readings of the same probe) was used as additive Gaussian measurement noise on every synthetic value, so that the synthetic samples carry the noise signature of the actual sensors rather than idealized values.

Fourth. A sample is labeled Ideal if and only if all three parameters lie within the tilapia band of Table 1, and Non-Ideal otherwise. This produced 152 Ideal (76%) and 48 Non-Ideal (24%) samples. Of the 48 Non-Ideal samples, most violate a single threshold, and the remainder violate two or three, so boundary-region and multi-violation states are both represented.

Fifth, Reproducibility should be secured. Generation used a fixed pseudo-random seed; the generator script and the resulting 200-row dataset are available from the corresponding author on request.

Table 1 Optimal water quality parameter ranges for catfish and tilapia in biofloc systems (labelling thresholds)

Parameter	Catfish (Clarias sp.) [10]	Tilapia (O. niloticus) [33], [5], [34]
Temperature (°C)	25 – 30	26 – 30
pH	6.5 – 8.5	6.5 – 8.5
Turbidity (NTU)	< 200	< 150

The synthetic set is used exclusively for evaluation (and, in the Scratch-FIS baseline and learning-curve experiments, for optimization of the baseline). The Transfer-FIS parameters are fixed from the literature before drawing any synthetic samples, so the dataset cannot bias its design. Three checks support the plausibility of the synthetic distribution: (i) the parameter ranges and noise levels are inherited from real biofloc measurements and real sensors; (ii) the Unadapted Source-FIS, which was designed on real catfish data and never exposed to the synthetic set, already reaches 97% accuracy on it (Section 4.2), which is consistent with the known ecological overlap of the two species and would not be expected if the synthetic distribution were pathological; and (iii) the synthetic Non-Ideal proportion (24%) is comparable to the proportion of out-of-range readings observed in the real catfish log (15%, three of 20). The remaining gap between synthetic and field distributions is acknowledged as a limitation (Section 5) and is the subject of ongoing field validation.

3.3 Knowledge Transfer Strategy

The proposed method is a parameter-level transfer. The structural components of the source FIS (rule base, inference engine, and defuzzification method) are retained without modification. Only the membership-function boundary parameters are adjusted to tilapia physiological tolerances, specifically the stricter turbidity threshold (<150 NTU vs. <200 NTU) and the elevated cold-temperature boundary (26°C vs. 25°C); the pH membership functions are unchanged because both species share the 6.5–8.5 band. Table 2 lists the trapezoidal parameters [a, b, c, d] of every input term for the source and the adapted models, and Fig. 2 plots the adapted functions. Note that shaded rows are the terms changed by transfer. The adapted system is hereafter referred to as the Transfer-FIS.

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Table 2 Trapezoidal membership-function parameters [a, b, c, d] of the source (catfish) FIS and the adapted Transfer-FIS (tilapia)

Input / term	Source-FIS (catfish)	Transfer-FIS (tilapia)
pH – Acid	[3, 3, 6.0, 6.5]	[3, 3, 6.0, 6.5]
pH – Neutral	[6.0, 6.5, 8.0, 8.5]	[6.0, 6.5, 8.0, 8.5]
pH – Alkali	[8.0, 8.5, 12, 12]	[8.0, 8.5, 12, 12]
Turbidity – Low	[0, 0, 100, 150]	[0, 0, 50, 100]
Turbidity – Intermediate	[100, 150, 150, 200]	[50, 100, 100, 150]
Turbidity – High	[150, 200, 250, 250]	[100, 150, 250, 250]
Temperature – Cold	[15, 15, 23, 25]	[15, 15, 24, 26]
Temperature – Intermediate	[23, 25, 28, 30]	[24, 26, 28, 30]
Temperature – Hot	[28, 30, 42, 42]	[28, 30, 42, 42]

3.4 Baseline Model (Scratch-FIS)

To quantify the benefit of transfer, a baseline FIS (Scratch-FIS) with the identical architecture (same inputs, three trapezoidal terms per input, same rule base, min–max inference, and centroid defuzzification) is constructed without any source-domain knowledge and optimized on tilapia data only. The procedure is as follows.

(1) Initialization. Each input universe of discourse is divided into three equal-width trapezoids (uniform partition) and every breakpoint (a, b, c, d) is perturbed by a random offset drawn uniformly from around 10% of the universe width, subject to the ordering constraint $a \leq b \leq c \leq d$. Ten independent random initializations (restarts) are generated.

(2) Objective. The macro-averaged F1-score on the training portion of the current fold (Section 3.5) is maximized; macro F1 is used rather than accuracy because of the 76/24 class imbalance.

(3) Search. From each initialization, a coordinate-wise local search is applied: each breakpoint is moved in turn by a step of 2% of the universe width in the direction that improves the objective, the step is halved when no improvement is found, and the search stops when the step falls below 0.25% of the universe width or after 200 iterations. The restart with the highest training-fold objective is retained.

(4) Control of leakage. Optimization uses training folds only; test folds are never seen during the search. The same pseudo-random seed is used for all experiments so that the Scratch-FIS and Transfer-FIS are compared on identical fold assignments and identical initial conditions.

For the learning-curve experiment (Section 3.5), the Transfer-FIS is additionally fine-tuned with the same local search but starting from the literature-derived parameters of Table 2 and with the search radius restricted to around 5% of the universe width, so that transfer knowledge is refined rather than discarded. The Scratch-FIS starts from the random initialization described above. Table 3 summarizes the settings.

Table 3 Optimization settings of the Scratch-FIS baseline and of Transfer-FIS fine-tuning

Setting	Scratch-FIS	Transfer-FIS (fine-tuning)
Initial parameters	Uniform partition + random offset (10% of universe)	Literature values (Table 2)
Search radius	Unrestricted (ordering $a \leq b \leq c \leq d$ only)	±5% of universe width
Objective	Macro F1 on training folds	Macro F1 on training folds
Search method	Coordinate-wise local search, 10 restarts	Coordinate-wise local search, 1 start
Step / stopping	2% of universe, halved on no gain; stop < 0.25% or 200 iterations	Same
Seed	Fixed (identical folds for all models)	Fixed

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3.5 Evaluation Protocol

Following the standard convention for alarm systems, Non-Ideal is the positive class. A true positive (TP) is a Non-Ideal sample correctly flagged; a false negative (FN) is a Non-Ideal sample classified as Ideal, i.e., a missed alarm; a false positive (FP) is an Ideal sample classified as Non-Ideal, i.e., a false alarm; and a true negative (TN) is an Ideal sample correctly accepted. Missed alarms are the safety-critical error (Section 3.9).

Model performance is assessed using accuracy, macro-averaged precision, recall, and F1-score on the full 200-sample set and across stratified 10-fold cross-validation (fold assignments identical for all models). Confusion-matrix counts (TP, FP, FN, TN) are reported explicitly.

A two-sided Wilcoxon signed-rank test ($\alpha = 0.05$) is applied to the paired fold accuracies of the Transfer-FIS and Scratch-FIS. The test can only assess whether a difference is detectable; a non-significant result does not establish equivalence, which would require an equivalence test with a pre-specified margin [35]. Accordingly, the paired mean difference and its standardized effect size (Cohen's d) are reported alongside the p-value, and the wording "no statistically significant difference was detected" is used throughout.

Model performance is evaluated as a function of the training-data fraction (10% to 100% in 10% increments, stratified), with the remaining data held out for testing at each fraction (learning curve).

3.6 Mamdani Fuzzy Inference System: Architectural Overview

The Mamdani-type FIS, first developed in 1975 to govern a steam engine using linguistically structured IF–THEN expert rules [36], serves as the reasoning engine for both the Transfer-FIS and the Scratch-FIS. Unlike the Takagi–Sugeno–Kang (TSK) system, which replaces fuzzy consequents with crisp functions and omits defuzzification for computational efficiency, the Mamdani architecture retains fully fuzzy consequents, preserving the linguistic interpretability that is critical for expert auditing in safety-sensitive biological monitoring [37].

The Mamdani FIS operates through four components: (1) the fuzzifier, which transforms crisp sensor readings into membership degrees; (2) the rule base, encoding domain-expert knowledge as IF–THEN statements; (3) the inference engine, which applies fuzzy operators to compute rule firing strengths; and (4) the defuzzifier, which converts the aggregated fuzzy output into a crisp classification value [37].

3.7 Mamdani FIS Processing Stages

Fuzzification transforms crisp IoT sensor measurements into membership degrees by evaluating each input against the membership functions of its linguistic variable. Each input is characterized by three overlapping terms. The trapezoidal membership function (trapMF) is parameterized by the vector [a, b, c, d] ($a \leq b \leq c \leq d$) and computed as:

$$f(x; a,b,c,d) = max\left(min\left(\frac{(x-a)}{(b-a)}, 1, \frac{(d-x)}{(d-c)}, 0 \right) \right) \quad (1)$$

This yields zero membership for $x \leq a$ or $x \geq d$, a linearly ascending slope for $a < x < b$, a constant maximum of 1.0 for $b \leq x \leq c$, and a descending slope for $c < x < d$. For the Transfer-FIS, only the scalar coordinates (a, b, c, d) are shifted along the x-axis to align with tilapia tolerances, while the functional form of Eq. (1) is unchanged [24].

The inference engine evaluates each IF–THEN rule against the fuzzified input vector. For antecedents linked by AND, the firing strength αk is computed with the minimum T-norm:

$$\alpha_k = min(\mu_{A1}(x_1), \mu_{A2}(x_2), \ldots, \mu_{An}(x_n)) \quad (2)$$

The implication step clips each active rule's consequent membership function at height αk using the Mamdani minimum (clipping) method:

$$\mu output_k(y) = min(\alpha k, \mu C(y)) \quad (3)$$

Clipping was selected for its computational efficiency in embedded IoT deployments, consistent with prior Mamdani aquaculture monitoring implementations [25].

Aggregation combines all k active rule outputs with the fuzzy union (maximum) operator:

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$$\mu Agg(y) = max(\mu output_1(y), \ldots, \mu output_k(y)) \quad (4)$$

The aggregate surface μAgg(y) is then defuzzified into a crisp scalar y* using the centroid-of-area (COA) method, discretised over n uniformly spaced points:

$$y^* = \frac{\sum(y_j \cdot \mu_{Agg}(y_j)}{\sum \mu_{Agg}(y_j)}, j = 1, \ldots, n \quad \ldots (5)$$

The COA method was selected for its holistic integration of all active rule contributions and is applied consistently across the Transfer-FIS and the Scratch-FIS [26].

3.8 Theoretical Basis for Parameter-Level Transfer

Under the definition of Pan and Yang [15], the source and target tasks here share the same feature space (pH, turbidity, temperature) and the same label space (Ideal/Non-Ideal); only the marginal distribution of the inputs and the conditional decision boundary differ because of species physiology. This is the setting in which parameter transfer is most effective [31], [32]: the macroscopic IF–THEN logic does not need to be reconstructed, and only the scalar thresholds that encode physiology require recalibration. This is operationalised as a +1°C elevation of the lower temperature boundary and a −50 NTU reduction of the turbidity shoulders (Table 2).

3.9 Safety Criterion: Asymmetric Cost of Misclassification

In aquaculture monitoring, misclassification errors carry asymmetric costs. A false negative, i.e., a genuinely Non-Ideal water state classified as Ideal, is the critical failure: automated alarms are suppressed, corrective action is delayed, and irreversible fish mortality may result. A false positive (a false alarm) costs an unnecessary inspection or water exchange but does not endanger the stock. Accordingly, minimisation of false negatives, equivalently maximisation of Non-Ideal recall, is adopted as the primary operational success criterion, consistent with the precautionary principle applied in safety-critical decision systems [32].

4 Results and Discussion

4.1 Source Model Re-Evaluation (Catfish Domain)

Re-scored under the harmonized threshold protocol (Section 3.1), the catfish source FIS achieved 85.00% accuracy on the 20 real sensor samples, with macro precision 0.7500, macro recall 0.9118, and macro F1 0.7849. All three errors are false negatives: the samples with pH 6.00, 6.15, and 6.20 fall in the overlap between the Acid and Neutral membership functions and are classified Ideal, whereas the harmonized rule labels them Non-Ideal. This boundary behaviour is expected of a fuzzy system and, importantly, marks the low-pH boundary as the region in which the source model is most permissive, which the transfer step must not inherit unchanged.



Fig. 1 Water quality monitoring and control system: (a) device housing; (b) water tanks.

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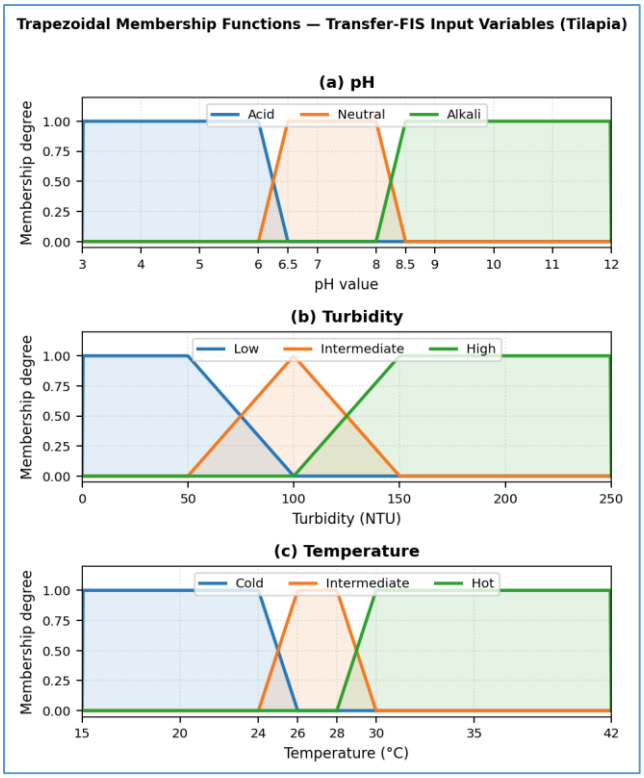


Fig. 2 Trapezoidal membership functions of the Transfer-FIS for (a) pH, (b) turbidity, and (c) temperature, parameterized with tilapia-specific thresholds (Table 2).

4.2 Domain Shift Assessment (Unadapted Source-FIS on Tilapia)

Applied directly to the tilapia dataset without adaptation, the source catfish FIS achieved 97.00% accuracy and macro F1 0.9595 (Table 4), reflecting the substantial overlap of the two species' water-quality envelopes. The six errors comprise four false alarms and two missed alarms (Table 5); the two missed alarms occur at turbidity values between 150 and 200 NTU, which are Ideal for catfish but Non-Ideal for tilapia. Species-specific threshold differences therefore introduce measurable and safety-relevant misclassification that targeted adaptation is expected to correct.

4.3 Transfer-FIS vs. Scratch-FIS Performance

Table 4 summarizes classification performance on the tilapia dataset and Table 5 gives the confusion-matrix counts with Non-Ideal as the positive class. The Transfer-FIS achieved 98.00% accuracy and the highest macro recall (0.9868), while the Scratch-FIS achieved marginally higher accuracy (98.50%) and precision (0.9903). The confusion matrices (Fig. 3) reveal the operationally most significant finding: the Transfer-FIS produces zero false negatives (all 48 Non-Ideal samples are flagged) at the cost of four false alarms, whereas the Scratch-FIS produces zero false alarms but misses three Non-Ideal samples. The adaptation step also removed both missed alarms of the Unadapted Source-FIS. In water-quality monitoring, missed alarms carry the highest operational risk because they suppress alerts during deteriorating conditions.

Table 4 Classification performance on the tilapia dataset (200 samples; macro-averaged precision, recall, and F1)

Model	Accuracy	Precision	Recall	F1-Score
Unadapted Source-FIS	0.9700	0.9533	0.9660	0.9595
Scratch-FIS	0.9850	0.9903	0.9688	0.9790
Transfer-FIS	0.9800	0.9615	0.9868	0.9733

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Table 5 Confusion-matrix counts with Non-Ideal as the positive class (48 Non-Ideal, 152 Ideal)

Model	TP	FP (false alarm)	FN (missed alarm)	TN
Unadapted Source-FIS	46	4	2	148
Scratch-FIS	45	0	3	152
Transfer-FIS	48	4	0	148

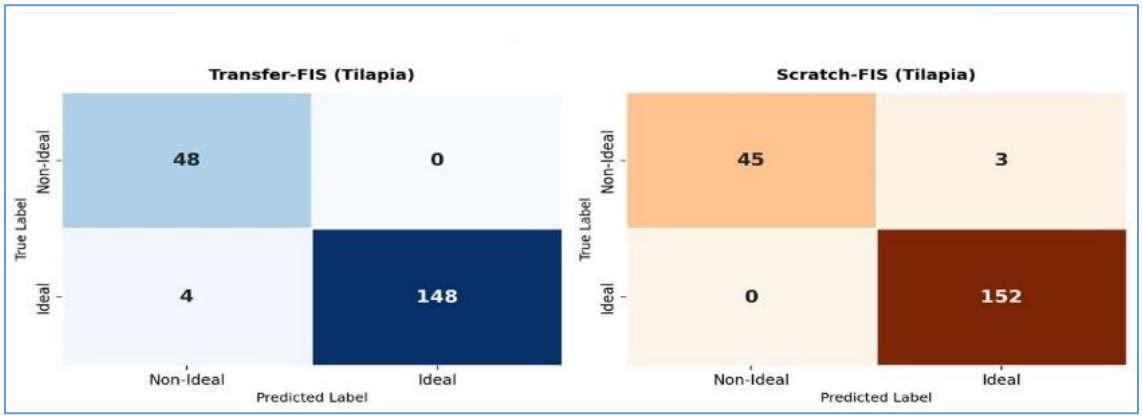


Fig. 3 Confusion matrices on the tilapia dataset: Transfer-FIS (left) and Scratch-FIS (right). Rows are true labels; columns are predicted labels. With Non-Ideal as the positive class, the Transfer-FIS has FN = 0 and FP = 4; the Scratch-FIS has FN = 3 and FP = 0.

4.4 Cross-Validation Results

Stratified 10-fold cross-validation yielded mean accuracies of 0.9800 ± 0.0245 for the Transfer-FIS and 0.9850 ± 0.0229 for the Scratch-FIS (paired mean difference 0.005 in favour of the Scratch-FIS). The Wilcoxon signed-rank test did not detect a statistically significant difference ($W = 2.0$, $p = 1.000$, $\alpha = 0.05$), and the standardized effect size is small (Cohen's $d \approx 0.21$). It should be stressed that this result indicates that a difference could not be detected with ten folds, not that the two models are equivalent; a formal equivalence claim would require a two one-sided tests procedure with a pre-registered margin and a larger number of folds [35]. Fig. 4 presents the fold-accuracy distributions.

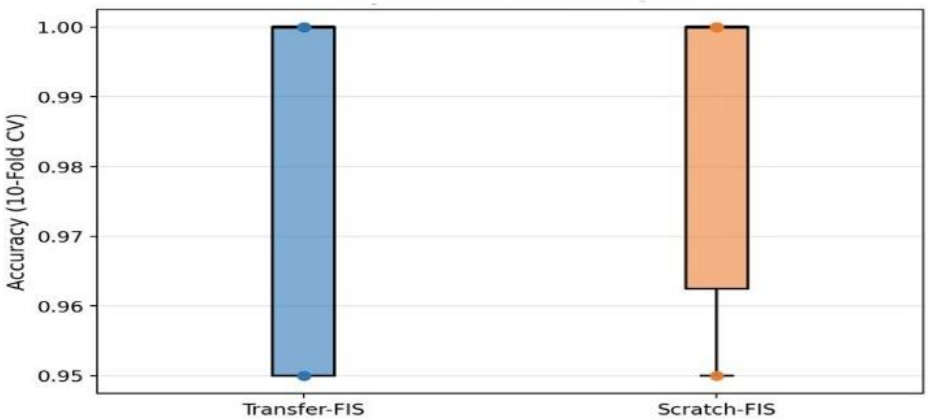


Fig. 4 Cross-validation accuracy distributions (10-fold). Wilcoxon signed-rank p = 1.000; Cohen's d ≈ 0.21.

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4.5 Performance Comparison Across All Models

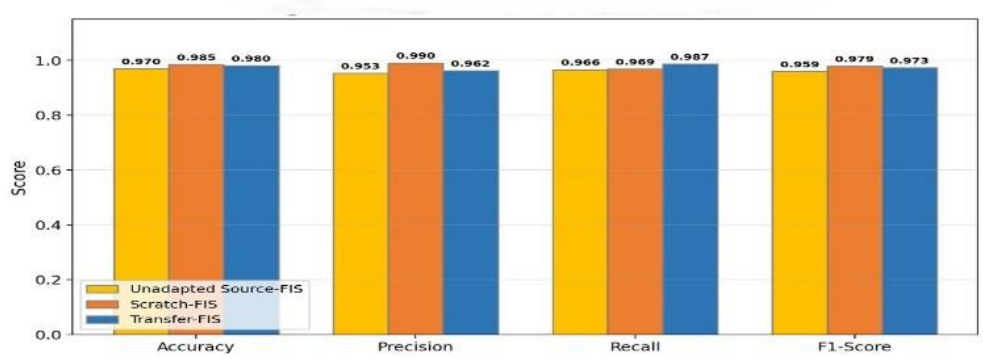


Fig. 5 Performance comparison (accuracy, macro precision, macro recall, macro F1) across the three models.

4.6 Learning Curve Analysis

Fig. 6 shows learning curves for both models as the tilapia training fraction increases from 10% to 100%. The Transfer-FIS reaches stable accuracy (~0.97) with as little as 10% of the data (20 samples), whereas the Scratch-FIS requires a substantially larger fraction before its accuracy stabilizes. This property is particularly valuable in aquaculture, where labelled sensor data for a new species are scarce and expensive to collect, and it is the practical manifestation of the transfer-learning premise that source knowledge reduces the target-domain sample requirement [15], [31].

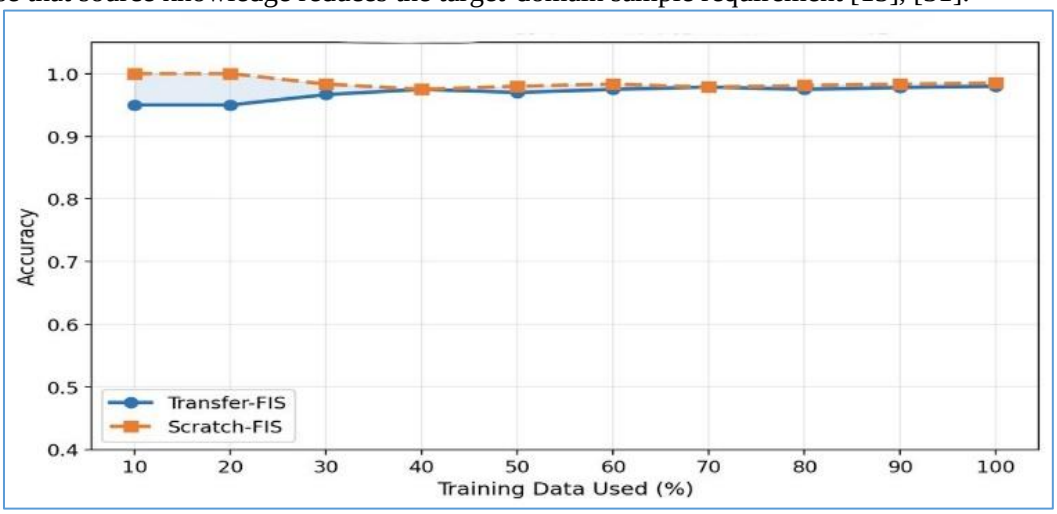


Fig. 6 Learning curve: Transfer-FIS vs. Scratch-FIS accuracy as a function of the training-data fraction.

5 Discussion

The results yield three principal findings. First, parameter-level fuzzy transfer performs on par with species-specific model design within the resolution of this experiment. The Transfer-FIS and Scratch-FIS produced cross-validation accuracies whose difference was not statistically detectable ($p = 1.000$, $d \approx 0.21$), indicating that adapting the membership-function boundaries of an existing fuzzy model is sufficient to achieve comparable performance on a new target species. This is consistent with theory: both species share the same three monitored parameters and the same classification schema, which are the conditions under which parameter transfer is expected to be effective [15], [31].

Second, the Transfer-FIS exhibits a more favourable error profile for safety. Although the Scratch-FIS marginally outperforms it in overall accuracy (98.5% vs. 98.0%) and precision, the Transfer-FIS produces zero missed alarms whereas the Scratch-FIS misses three Non-Ideal states. A missed alarm is a failure to warn the farmer of deteriorating water, allowing quality to decline unchecked until fish health is compromised. The conservative behaviour of the Transfer-FIS, inherited from the catfish model's rule structure and reinforced by the tightened turbidity shoulder,

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provides an ecologically meaningful safety margin. The price is four false alarms in 200 samples (2%), an acceptable operational cost.

Third, transfer learning reduces target-domain data dependency. The learning curves show that the Transfer-FIS reaches near-peak performance with 20 tilapia samples, while the Scratch-FIS requires proportionally more data to stabilize. This has direct implications for Indonesian aquaculture, where monitoring infrastructure for less-studied species may not yet support large data-collection campaigns.

It is also notable that the unadapted catfish FIS already achieves 97.00% on the tilapia data, reflecting the ecological similarity of the two species. The incremental benefit of adaptation (97.00% to 98.00%) is modest in accuracy but decisive in safety terms: adaptation eliminated the two missed alarms of the unadapted model.

What is the validity of the synthetic evaluation? The central methodological question is whether conclusions drawn on a literature-anchored synthetic dataset transfer to field conditions. Three arguments support a cautious positive answer. (i) The Transfer-FIS is knowledge-driven and was fixed before the data were generated, so the synthetic set functions as a verification test bench rather than as training data; its outcomes measure whether the transferred decision surface reproduces literature-defined tilapia tolerances across the full operating envelope, exactly as randomized simulation is used to verify controllers before deployment [16], [17]. (ii) The synthetic distribution is anchored to real ranges and to the noise of real sensors, and an independent model that never saw it (the Unadapted Source-FIS) behaves on it as ecological knowledge predicts. (iii) The approach follows Scopus-indexed precedent in medicine [18], smart farming [19], small-data aquatic modelling [14], and tilapia decision support specifically [20]. The residual reality gap, arising for example from sensor drift, biofloc-induced turbidity dynamics, and diurnal correlation among parameters that independent sampling does not capture, cannot be quantified without field data. Consequently, the claims of this paper are limited to the transferability of fuzzy decision logic under literature-defined conditions; absolute field accuracies should not be inferred from the reported values.

Limitations are known. The tilapia dataset is synthetically generated (Section 3.2) rather than collected in an active biofloc pond, and field validation is required to quantify the reality gap. The catfish source dataset comprises 20 samples from a single monitoring day, limiting the diversity of environmental conditions captured. The cross-validation comparison has limited statistical power (ten folds), so the absence of a detected difference should not be read as equivalence. Finally, only three parameters are monitored; dissolved oxygen and total ammonia nitrogen would provide a more comprehensive biofloc water-quality model.

6 Conclusion

This study presented a transfer-learning framework for water-quality classification in tilapia (Oreochromis niloticus) biofloc systems, using a validated catfish (Clarias gariepinus) fuzzy inference system as the source-domain model. The Transfer-FIS adapts the source model's membership-function boundaries to tilapia physiological thresholds without modifying the rule base or inference structure, and was evaluated on a literature-anchored synthetic test bench whose validity is argued from the knowledge-driven nature of the FIS, from simulation-to-real precedent, and from consistency checks against a model designed on real data.

Key findings are as follows. First, the Transfer-FIS achieves 98.00% accuracy and macro F1 = 0.9733; no statistically significant difference from the Scratch-FIS (98.50%, F1 = 0.9790) was detected (Wilcoxon $p = 1.000$, Cohen's $d \approx 0.21$). Second, with Non-Ideal as the positive class, the Transfer-FIS produces zero false negatives (missed alarms), the safety-critical error in aquaculture monitoring, whereas the Scratch-FIS produces three. Third, the Transfer-FIS reaches near-peak performance with as few as 20 tilapia samples. Together these results indicate that parameter-level fuzzy transfer is a viable, data-efficient, and operationally conservative strategy for extending aquaculture monitoring systems across fish species.

The practical contribution is significant in resource-limited aquaculture: operators with an existing fuzzy monitoring system for one species can adapt it to a new species by recalibrating membership-function boundaries from published literature, without a complete redesign or a large

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data-collection campaign. This is particularly relevant in Indonesia, where catfish and tilapia are both widely cultivated but monitoring systems have historically been developed in isolation.

Future work includes: (1) validation on IoT-collected tilapia sensor data from operational biofloc farms to quantify the synthetic-to-field reality gap, with equivalence testing at a pre-specified margin; (2) extension of the parameter set to dissolved oxygen and total ammonia nitrogen; (3) evaluation of the framework for additional species such as freshwater prawn (Macrobrachium rosenbergii); and (4) automated membership-function adaptation using metaheuristic optimization to reduce the manual domain-expertise requirement.

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References

[1] P. A. Indriati and H. Hafiludin, "Manajemen Kualitas Air pada Pembenihan Ikan Nila (*Water Quality Management in Nile Tilapia Hatchery*)," Juvenil: Jurnal Ilmiah Kelautan dan Perikanan, Vol. 3, No. 2, 2022, DOI: 10.21107/juvenil.v3i2.15812.

[2] M. S. El-Sherif and A. M. I. El-Feky, "*Performance of Nile Tilapia (Oreochromis Niloticus) Fingerlings. I. Effect of pH*," International Journal of Agriculture and Biology, Vol. 11, No. 3, pp. 297–300, 2009.

[3] A. J. Makori, P. O. Abuom, R. Kapiyo, D. N. Anyona, and G. O. Dida, "*Effects of Water Physico-Chemical Parameters on Tilapia (Oreochromis Niloticus) Growth in Earthen Ponds in Teso North Sub-County, Busia County*," Fisheries and Aquatic Sciences, Vol. 20, Art. No. 30, 2017, DOI: 10.1186/s41240-017-0075-7.

[4] E. Pitowarno et al., "*Design and Development Smart Aquaculture in Freshwater Pond based on Fuzzy Logic*," BIO Web of Conferences, Vol. 80, Art. No. 06001, 2023, DOI: 10.1051/bioconf/20238006001.

[5] G. B. Martins, C. E. da Rosa, F. de M. Tarouco, and R. B. Robaldo, "*Growth, Water Quality and Oxidative Stress of Nile Tilapia (Oreochromis Niloticus) in Biofloc Technology System at Different pH*," Aquaculture Research, Vol. 50, No. 6, pp. 1919–1929, 2019, DOI: 10.1111/are.13975.

[6] M. A. Baker Siddique et al., "*Impact of Climatic Factors on Water Quality Parameters in Tilapia Broodfish Ponds*," Heliyon, Vol. 10, Art. No. e37717, 2024, DOI: 10.1016/j.heliyon.2024.e37717.

[7] F. H. Azhra and C. Anam, "*IoT-based Automatic Fish Pond Control System*," IPTEK Journal of Proceedings Series, No. 6, 2021, DOI: 10.12962/j23546026.y2020i6.11128.

[8] H. Cumming and N. A. Herbert, "*Gill Structural Change in Response to Turbidity has no Effect on the Oxygen Uptake of a Juvenile Sparid Fish*," Conservation Physiology, Vol. 4, No. 1, Art. No. cow033, 2016, DOI: 10.1093/conphys/cow033.

[9] W. Sung, I. G. Tofik Isa, and S. Hsiao, "*An IoT-based Aquaculture Monitoring System using Firebase*," Computers, Materials & Continua, 2023, DOI: 10.32604/cmc.2023.041022.

[10] M. A. Hidayat et al., "*Water Quality Monitoring for Catfish Biofloc using Fuzzy Decision*," in Proc. 2024 5th Int. Conf. Smart Sensors and Application (ICSSA), 2024, pp. 1–6, DOI: 10.1109/ICSSA62312.2024.10788548.

[11] S. Nasr-Allah, A. M. Nasr-Allah, K. I. Kashem, M. A. Zaki, A. Khafaga, and M. S. Abuowarda, "*Effect of Environmental Factors on Growth Performance of Nile Tilapia (Oreochromis Niloticus)*," International Journal of Biometeorology, Vol. 66, No. 11, pp. 2183–2194, 2022, DOI: 10.1007/s00484-022-02347-6.

[12] E. El-Shafeiy, M. Alsabaan, M. I. Ibrahem, and H. Elwahsh, "*Real-Time Anomaly Detection for Water Quality Sensor Monitoring based on Multivariate Deep Learning Technique*," Sensors, Vol. 23, No. 21, Art. No. 8613, 2023, DOI: 10.3390/s23218613.

[13] D. Hidayati, S. D. Nurtjahyani, D. Oktafitria, N. M. Ashuri, and W. Kurniallah, "*Evaluation of Water Quality and Survival Rate of Red Tilapia (Oreochromis Niloticus) by using Rice-Fish*

 ISSN:2302-8149
e-ISSN:2540-9719

Culture System in Quarry Land of Clay," Biodiversitas Journal of Biological Diversity, Vol. 20, No. 2, pp. 589–594, 2019, DOI: 10.13057/biodiv/d200240.

[14] Y. Chen, L. Liu, and D. Gao, "*Machine Learning for Small-Data in Aquatic Environments: A Review of Challenges, Methods, and Optimization Approaches*," ENGINEERING Environment (Formerly Frontiers of Environmental Science & Engineering), Vol. 20, No. 6, Art. No. 86, 2026, DOI: 10.1007/s11783-026-2186-9.

[15] S. J. Pan and Q. Yang, "*A Survey on Transfer Learning*," IEEE Transactions on Knowledge and Data Engineering, Vol. 22, No. 10, pp. 1345–1359, 2010, DOI: 10.1109/TKDE.2009.191.

[16] J. Tobin, R. Fong, A. Ray, J. Schneider, W. Zaremba, and P. Abbeel, "*Domain Randomization for Transferring Deep Neural Networks from Simulation to the Real World*," in Proc. IEEE/RSJ Int. Conf. Intelligent Robots and Systems (IROS), 2017, pp. 23–30, DOI: 10.1109/IROS.2017.8202133.

[17] F. Muratore, F. Ramos, G. Turk, W. Yu, M. Gienger, and J. Peters, "*Robot Learning from Randomized Simulations: A Review*," Frontiers in Robotics and AI, Vol. 9, Art. No. 799893, 2022, DOI: 10.3389/frobt.2022.799893.

[18] R. J. Chen, M. Y. Lu, T. Y. Chen, D. F. K. Williamson, and F. Mahmood, "*Synthetic Data in Machine Learning for Medicine and Healthcare*," Nature Biomedical Engineering, Vol. 5, No. 6, pp. 493–497, 2021, DOI: 10.1038/s41551-021-00751-8.

[19] Y. Akkem, S. K. Biswas, and A. Varanasi, "*A Comprehensive Review of Synthetic Data Generation in Smart Farming by using Variational Autoencoder and Generative Adversarial Network*," Engineering Applications of Artificial Intelligence, Vol. 131, Art. No. 107881, 2024, DOI: 10.1016/j.engappai.2024.107881.

[20] A. M. Alnemari et al., "*Developing Highly Accurate Machine Learning Models for Optimizing Water Quality Management Decisions in Tilapia Aquaculture*," Scientific Reports, Vol. 15, Art. No. 35600, 2025, DOI: 10.1038/s41598-025-16939-w.

[21] Y. Ma, S. Chen, S. Ermon, and D. B. Lobell, "*Transfer Learning in Environmental Remote Sensing*," Remote Sensing of Environment, Vol. 301, Art. No. 113924, 2024, DOI: 10.1016/j.rse.2023.113924.

[22] M. Zhu et al., "*A Review of the Application of Machine Learning in Water Quality Evaluation*," Eco-Environment & Health, Vol. 1, No. 2, pp. 107–116, 2022, DOI: 10.1016/j.eehl.2022.06.001.

[23] I. Essamlali, H. Nhaila, and M. El Khaili, "*Advances in Machine Learning and IoT for Water Quality Monitoring: A Comprehensive Review*," Heliyon, Vol. 10, No. 6, Art. No. e27920, 2024, DOI: 10.1016/j.heliyon.2024.e27920.

[24] L. A. Zadeh, "*The Concept of a Linguistic Variable and Its Application to Approximate Reasoning*," Information Sciences, Vol. 8, No. 3, pp. 199–249, 1975, DOI: 10.1016/0020-0255(75)90036-5.

[25] S. K. Nagothu, P. Bindu Sri, G. Anitha, S. Vincent, and O. P. Kumar, "*Advancing Aquaculture: Fuzzy Logic-based Water Quality Monitoring and Maintenance System for Precision Aquaculture*," Aquaculture International, Vol. 33, Art. No. 32, 2025, DOI: 10.1007/s10499-024-01701-2.

[26] M. R. D. Molato, "*AquaStat: An Arduino-based Water Quality Monitoring Device for Fish Kill Prevention in Tilapia Aquaculture using Fuzzy Logic*," International Journal of Advanced Computer Science and Applications, Vol. 13, No. 2, pp. 557–562, 2022, DOI: 10.14569/IJACSA.2022.0130265.

[27] M. Bautista, M. Palconit, M. Rosales, and R. Concepcion II, "*Fuzzy Logic-based Adaptive Aquaculture Water Monitoring System based on Instantaneous Limnological Parameters*," Journal of Advanced Computational Intelligence and Intelligent Informatics, Vol. 26, No. 6, pp. 937–943, 2022, DOI: 10.20965/jaciii.2022.p0937.

[28] Y. Barzegar, I. Gorelova, F. Bellini, and F. D'Ascenzo, "*Drinking Water Quality Assessment using a Fuzzy Inference System Method: A Case Study of Rome (Italy)*," International Journal of Environmental Research and Public Health, Vol. 20, No. 10, Art. No. 6522, 2023, DOI: 10.3390/ijerph20106522.

[29] M. Qulub, M. Fahruddin, M. S. Rizki, and A. Saputra, "*Automation of Water Quality Recovery in Vannamei Shrimp Aquaculture using the KNN Algorithm and Fuzzy Logic*," SISTEMASI, Vol. 15, No. 3, pp. 844–855, 2026, DOI: 10.32520/stmsi.v15i3.5888.

 ISSN:2302-8149
e-ISSN:2540-9719

[30] K. P. Rasheed Abdul Haq and V. P. Harigovindan, "*Water Quality Prediction for Smart Aquaculture using Hybrid Deep Learning Models*," IEEE Access, Vol. 10, pp. 60078–60098, 2022, DOI: 10.1109/ACCESS.2022.3180482.
[31] J. Lu, H. Zuo, and G. Zhang, "*Fuzzy Multiple-Source Transfer Learning*," IEEE Transactions on Fuzzy Systems, Vol. 28, No. 12, pp. 3418–3431, 2020, DOI: 10.1109/TFUZZ.2019.2952792.
[32] K. Li, J. Lu, H. Zuo, and G. Zhang, "*Source-Free Multi-Domain Adaptation with Fuzzy Rule-based Deep Neural Networks*," IEEE Transactions on Fuzzy Systems, Vol. 31, No. 12, pp. 4180–4194, 2023, DOI: 10.1109/TFUZZ.2023.3276978.
[33] M. E. Azim and D. C. Little, "*The Biofloc Technology (BFT) in Indoor Tanks: Water Quality, Biofloc Composition, and Growth and Welfare of Nile Tilapia (Oreochromis Niloticus)*," Aquaculture, Vol. 283, No. 1–4, pp. 29–35, 2008, DOI: 10.1016/j.aquaculture.2008.06.036.
[34] G. Abakari et al., "*The Use of Biochar in the Production of Tilapia (Oreochromis Niloticus) in a Biofloc Technology System – BFT*," Aquacultural Engineering, Vol. 91, Art. No. 102123, 2020, DOI: 10.1016/j.aquaeng.2020.102123.
[35] D. Lakens, "*Equivalence Tests: A Practical Primer for t Tests, Correlations, and Meta-Analyses*," Social Psychological and Personality Science, Vol. 8, No. 4, pp. 355–362, 2017, DOI: 10.1177/1948550617697177.
[36] E. H. Mamdani and S. Assilian, "*An Experiment in Linguistic Synthesis with a Fuzzy Logic Controller*," International Journal of Man-Machine Studies, Vol. 7, No. 1, pp. 1–13, 1975, DOI: 10.1016/S0020-7373(75)80002-2.
[37] C. C. Lee, "*Fuzzy Logic in Control Systems: Fuzzy Logic Controller—Parts I and II*," IEEE Transactions on Systems, Man, and Cybernetics, Vol. 20, No. 2, pp. 404–435, 1990, DOI: 10.1109/21.52551.